Steering Angle
Lane masking and Curvature

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Automotive

Overview

Lane Based Steering Angle Estimation

Background :

- Lane detection is a core component of autonomous driving
- Traditional methods (thresholding, edge detection) are sensitive to:
    - Lighting changes
    - Shadows
    - Complex road textures
- Deep learning enables robust pixel-level understanding of the road

Project Objectives

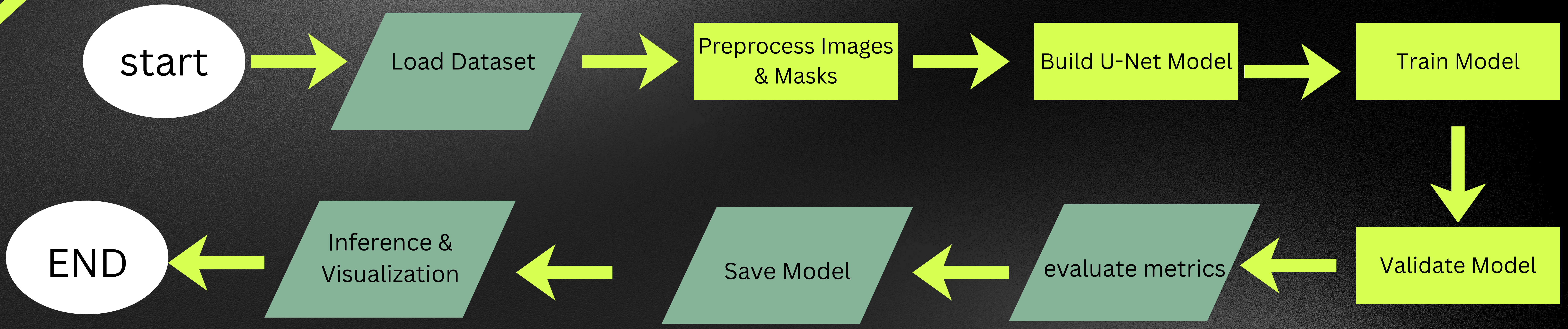
- Design a computer vision system for lane curvater and angle estimation
- Perform lane segmentation using deep learning

Overview

System Overview (pipline) :

- Camera Image (stereo vision)
- Preprocessing
- U-Net Segmentation
- Lane Mask
- Boundary Extraction
- Steering Angle Estimation (next stage)

Flowchart



start
Load Dataset
Preprocess Images & Masks
Build U-Net Model
Train Model
Validate Model
evaluate metrics
Save Model
Inference & Visualization
END

Datasets

- Dataset from Roboflow
- Data type: Image–Mask pairs

  - RGB road images

  - Binary lane masks
- Dataset split into:

  - Training set

  - Validation set

Label Definition
White (1): Lane / drivable area
Black (0): Background

Characteristics

- RGB road images
- Binary segmentation masks:
  - Lane area (white)
  - Background (black)

DATA PREPROCESSING

Image Preprocessing

- Resize images to 256 × 256
- Normalize pixel values to [0, 1]

Mask Preprocessing

- Convert to grayscale
- Binarization using threshold > 0.5
- Expand dimensions to match model output

```
# --- image ---
img = Image.open(img_path).convert("RGB")
img = img.resize((img_size, img_size))
img = np.array(img, dtype=np.float32) / 255.0
```

Preprocessing steps in this project:

- Encoder extracts lane features
- Decoder reconstructs segmentation mask
- Skip connections preserve spatial details

Output layer:

- 1 channel
- Sigmoid activation

Model Architecture

Base model: U-Net (Encoder–Decoder CNN)

Key components:

- Encoder: extracts hierarchical features
- Bottleneck: compact feature representation
- Decoder: reconstructs spatial details

Skip connections: preserve fine lane boundaries

Feature extraction happen inside the convolution blocks (it learn edges,texture , road geometry)

Model Architecture

U-net Modified

Although inspired by the original U-Net, this implementation includes task-specific modifications:

1. **Binary Output Channel**
   - Output layer uses 1 channel only
   - Designed specifically for binary lane vs background segmentation
2. **Sigmoid Activation at Output**
   - Produces pixel-wise probabilities in range [0, 1]
   - Enables simple thresholding for lane mask generation
3. **Lightweight Architecture**
   - Reduced depth and filter size compared to full U-Net
   - Optimized for real-time inference and limited GPU memory
4. **Training from Scratch**
   - No pretrained weights are used
   - All convolution layers are learned directly from the dataset

Training (custom u-net)

Base model: U-Net (Encoder–Decoder CNN)

Key components:

- **Encoder: extracts hierarchical features**
- **Bottleneck: compact feature representation**
- **Decoder: reconstructs spatial details**
- **Skip connections: preserve fine lane boundaries**

- **Training:**
  - **Epochs: 75**
  - **Small batch size (2) due to limited GPU memory**
- **Training Configuration**
- Optimizer: Adam
- Loss Function: Binary Cross-Entropy
- Metrics:
  - Accuracy , Precision , Recall

DATA PIPELINE

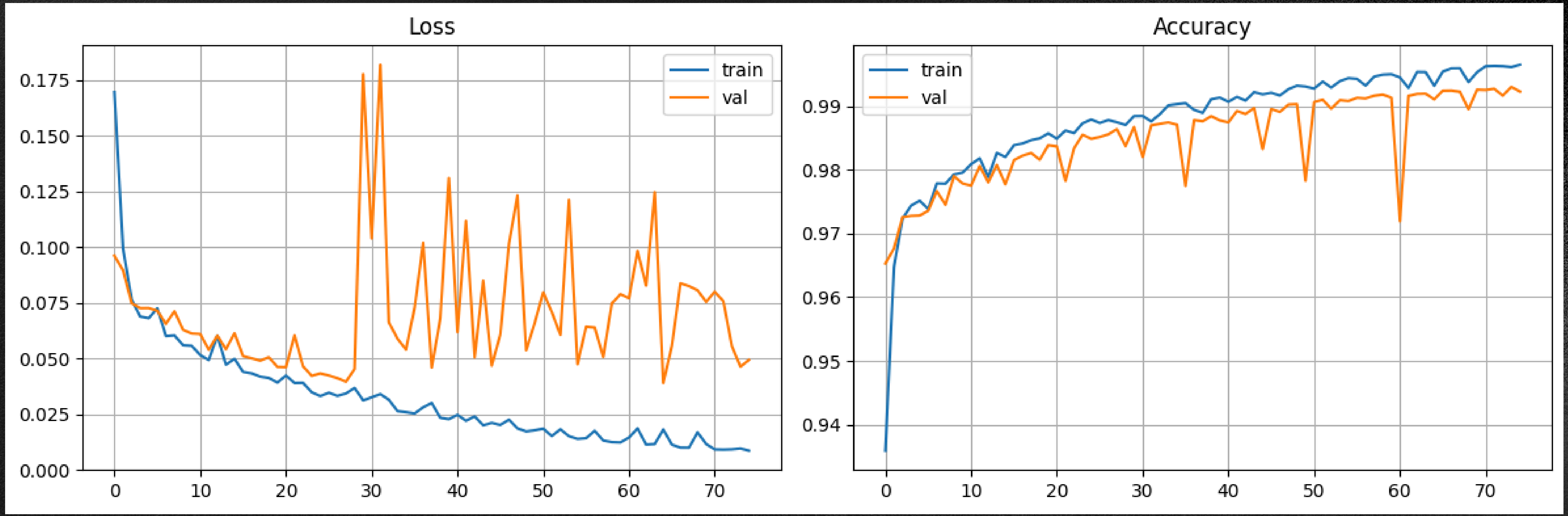
Input Road Image → Image Resizing & Normalization → Convert masks to binary format → Create TensorFlow Dataset → Shuffle, batch, and prefetch data → Feed data into U-Net model for training

Training Results

Training Performance

- Training loss decreases steadily
- Validation loss remains stable
- Accuracy reaches above 99%
- No significant overfitting observed

The model shows strong convergence and stability.



Training Results

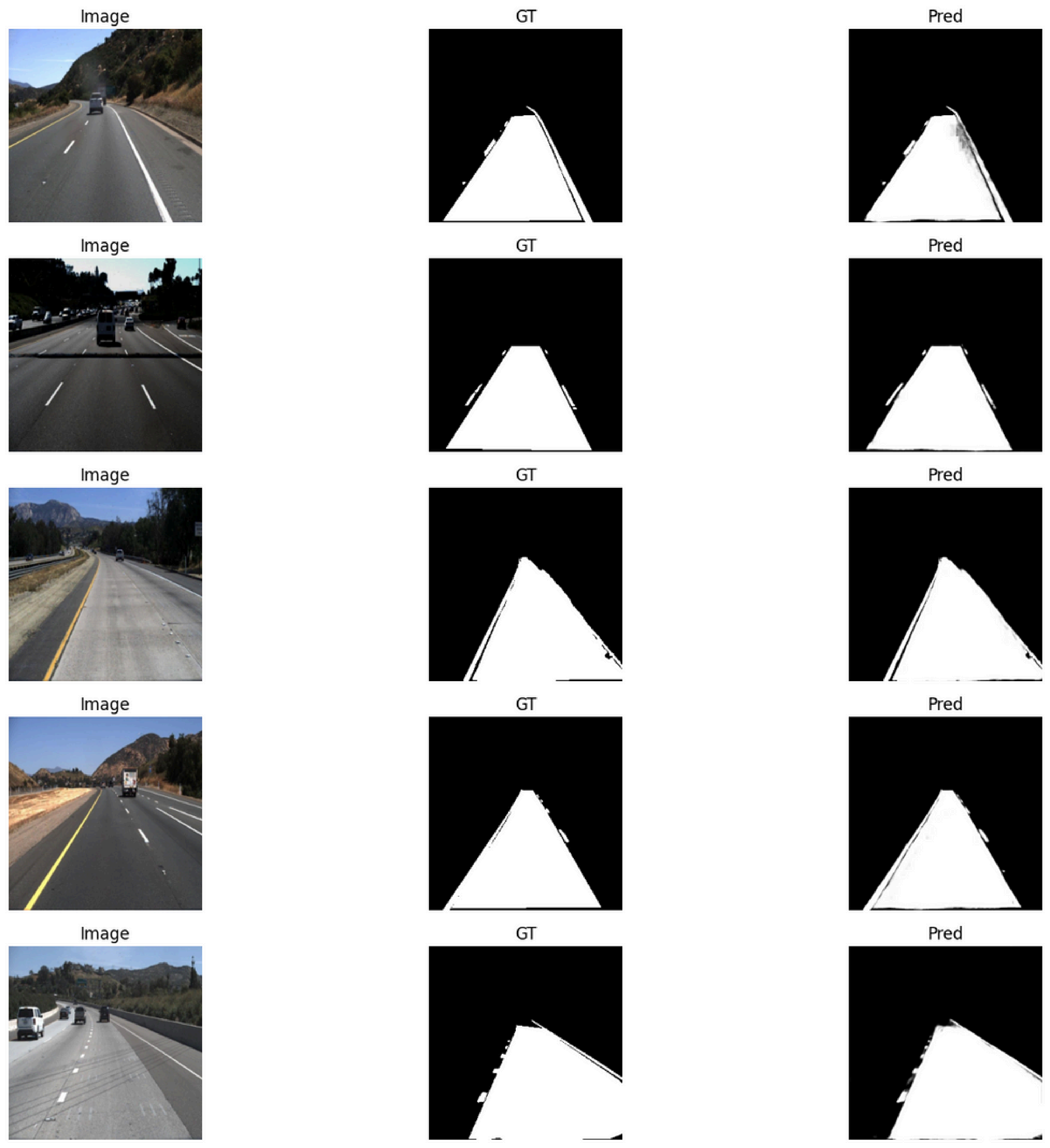
- Predicted lane masks closely match ground truth
- Accurate segmentation across:
  - Straight roads
  - Curved lanes
  - Different lighting conditions

This demonstrates strong generalization ability.

Model Evaluation

- High segmentation accuracy
- Good precision and recall
- Consistent validation performance

Evaluation confirms the model is reliable for lane detection.



- **Dataset not from stereo camera**

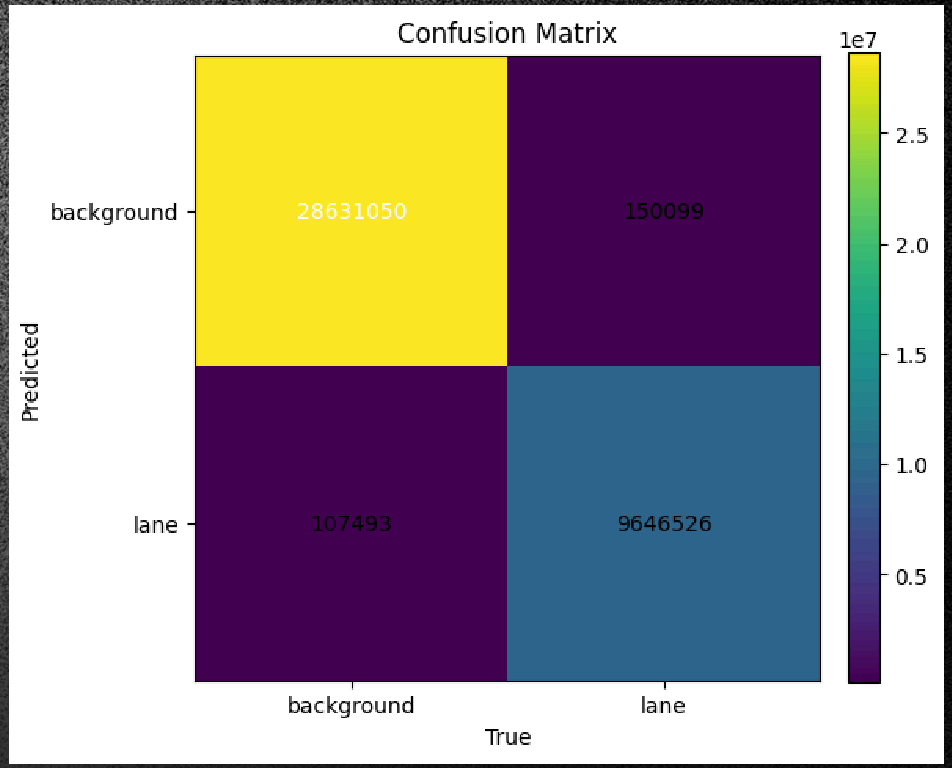
Training Results

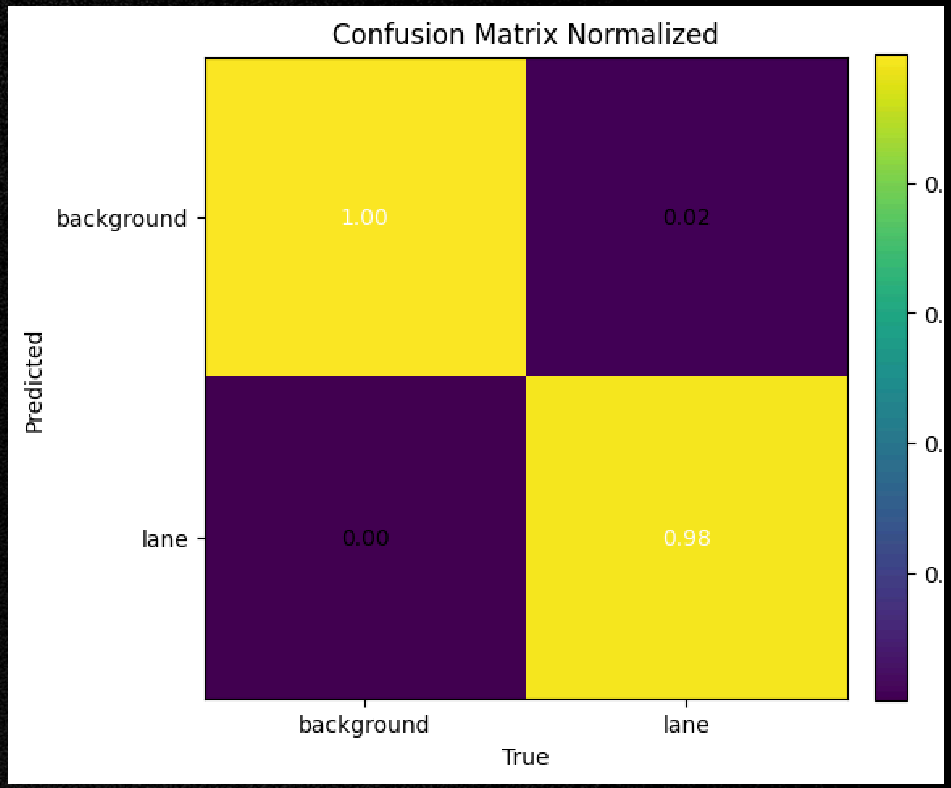
Classes

- Background
- Lane

Insights

- **High true positive rate for lane pixels**
- **Very low false positives**
- **Balanced classification across classes**





Model Evaluation (Validation Set)

Accuracy : 0.9933
Precision : 0.9847
Recall : 0.9890
F1-Score : 0.9868
IoU (Lane) : 0.9740
Dice (Lane): 0.9868

conclusions

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- Accurate segmentation across:
    - Straight roads
    - Curved lanes
    - Different lighting conditions

This demonstrates strong generalization ability.

Model Evaluation

- High segmentation accuracy
- Good precision and recall
- Consistent validation performance

Evaluation confirms the model is reliable for lane detection, but **in wet road model is unreliable due to reflection.**

Sensor Fusion Principles & Components

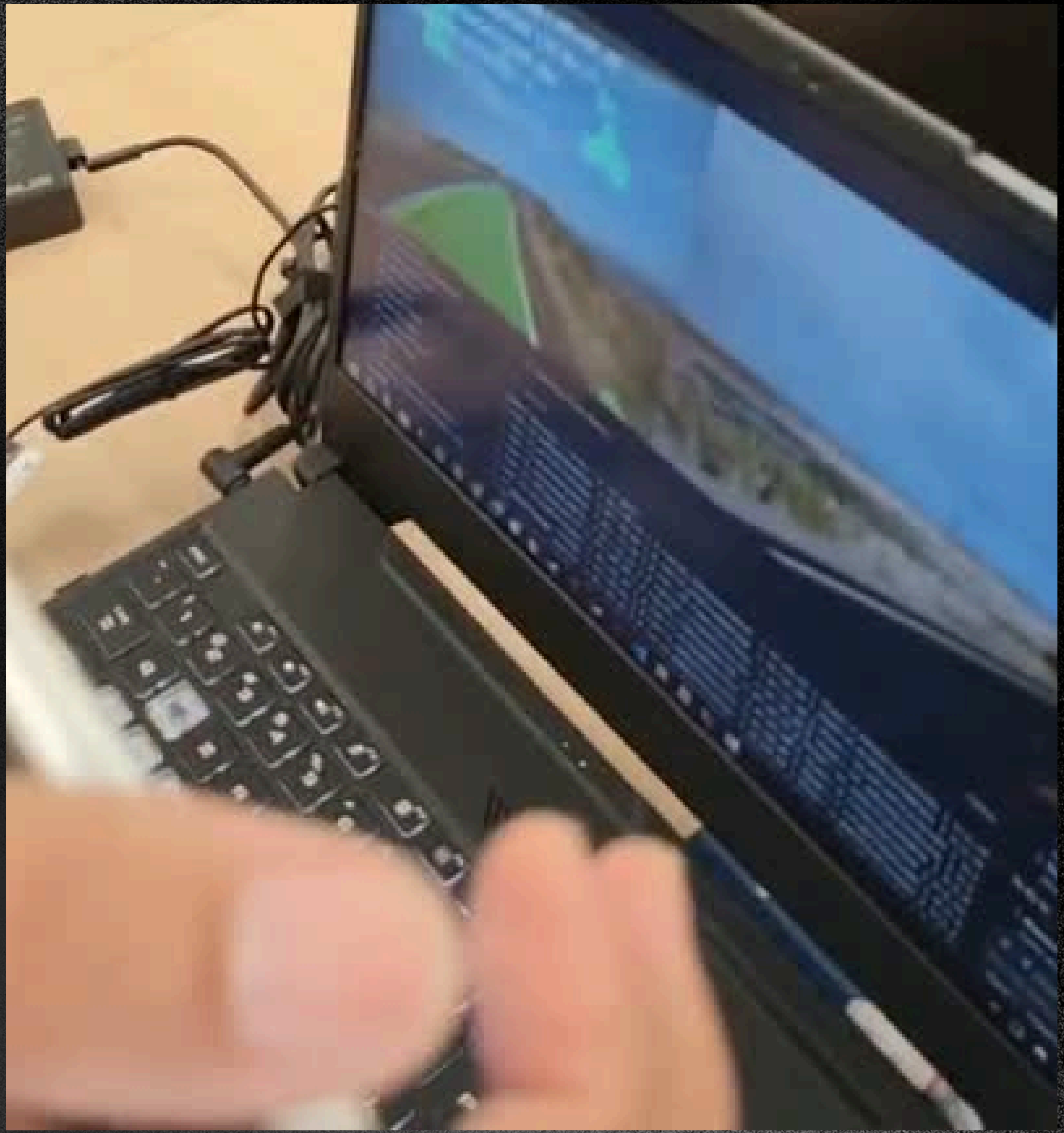
Limitations

- No explicit data augmentation (could improve robustness)
- Binary segmentation only (does not separate left/right lane boundaries)
- Performance depends on dataset diversity

Future work

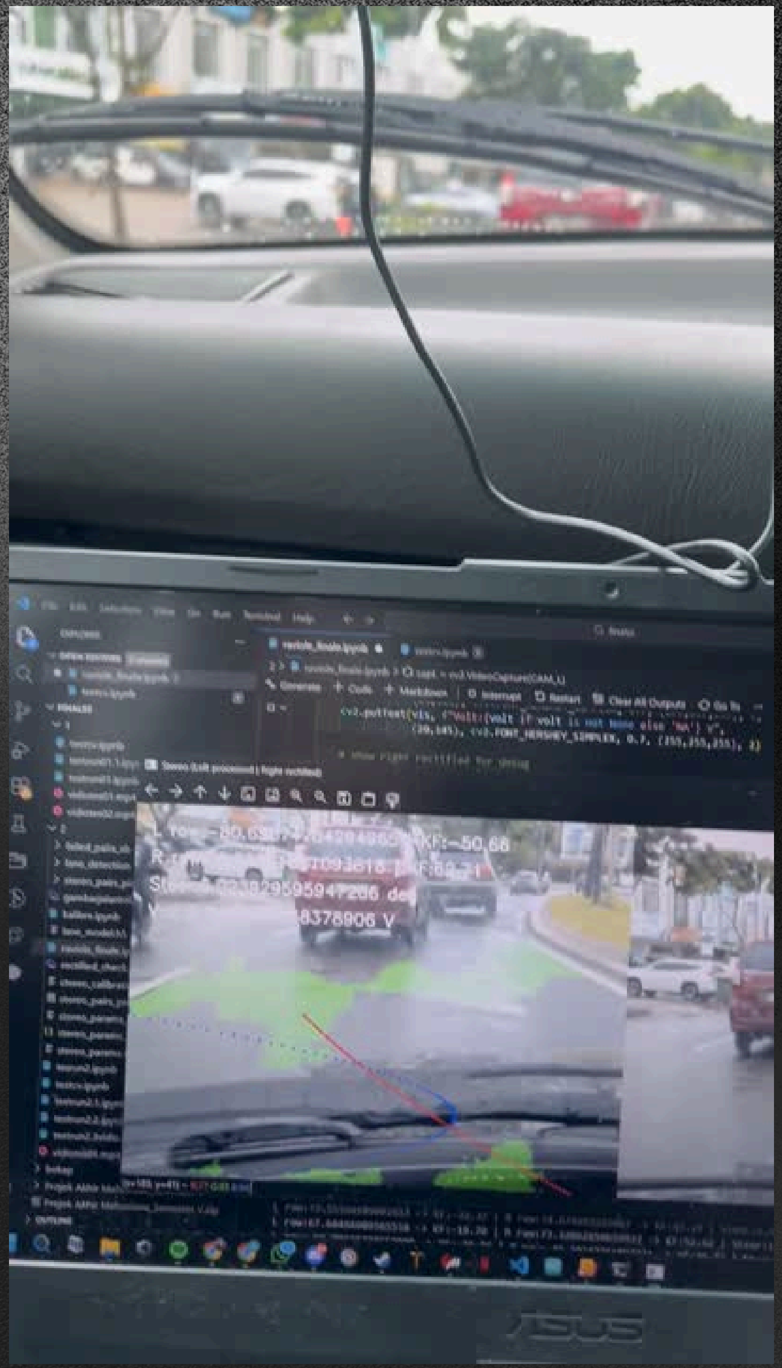
- Add augmentation: brightness/contrast, blur, shadow simulation
- Train multi-class (left lane/right lane/road/background)
- Optimize for real-time inference and deployment

Results



- Vision-based lane detection combined with Kalman Filter
- Demonstrates practical sensor fusion for vehicle control

Results



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Sensor Fusion for Vehicle

Sensor Fusion Principles & Components

System Overview

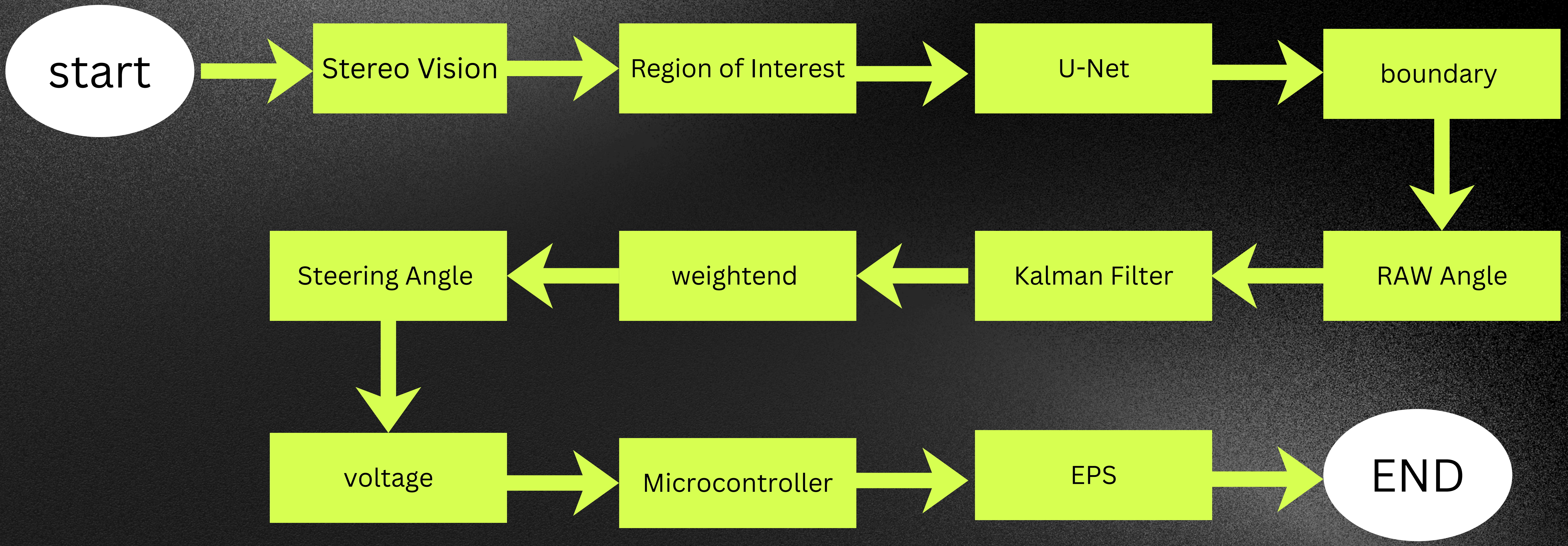
- Sensor: Stereo Vision Camera (2 webcams)
- Perception Model: Semantic Segmentation (U-Net)
- Feature Extraction: Lane boundary detection
- Estimation Layer: Kalman Filter
- Control Output: Steering Angle & Voltage

Objective:

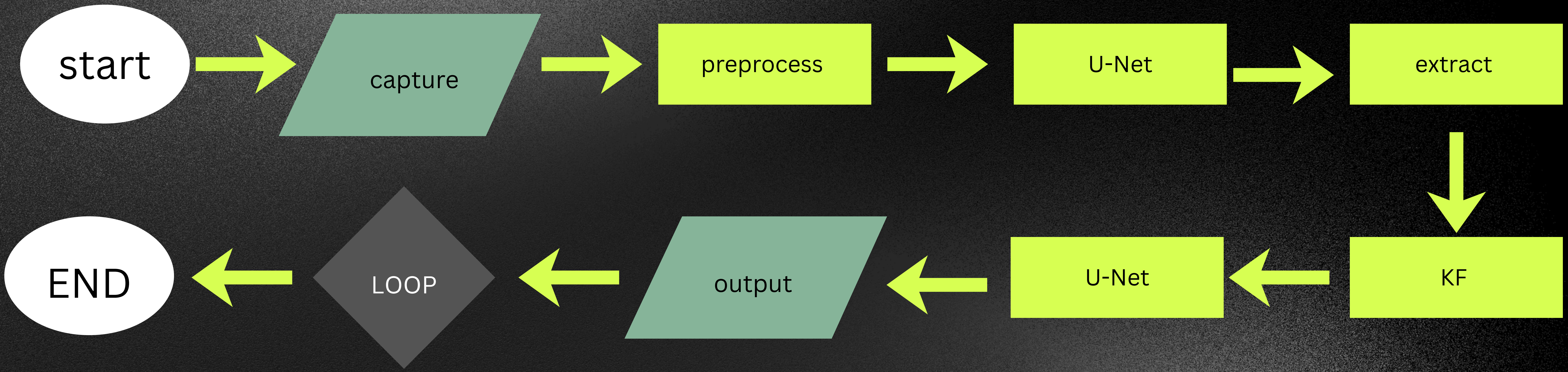
- Stereo camera → lane perception
- Kalman Filter → noise reduction
- Angle estimator → output

Stereo Camera → U-Net Segmentation → Lane Boundary → Angle Measurement → Kalman Filter → Fusion → θ_steer → Command (MCU/EPS)

Block Diagram



Flowchart


start
capture
preprocess
U-Net
extract
KF
U-Net
output
LOOP
END

Linear & Nonlinear Models

Nonlinear Models

- Convolutional Neural Network (U-Net) (Mengubah gambar jalan menjadi binary lane mask)
- Polynomial curve fitting (2nd order)
- Angle computation

Linear Models

- Kalman Filter (state-space linear model)
- Steering angle to voltage mapping (linear scaling)

State-Space Modeling

State Equation

The steering angle estimation is modeled as:

$$x_k = x_{k-1} + w_k$$

Measurement Equation:

$$z_k = x_k + v_k$$

xk = sudut sebenarnya pada frame camera ke-k
xk−1 = sudut pada frame camera sebelumnya
wk = noise proses (perubahan kecil antar frame camera)
zk = hasil pengukuran sensor (stereo camera)
vk = noise sensor

Kalman Filter Development

2D Discrete Kalman Filter

Prediction

Input Kalman Filter:
zL(k): sudut boundary kiri
zR(K): sudut boundary kanan

Update

Steering Angle Estimation:

- Adjustable weights allow confidence tuning
- Output is converted to steering voltage

Data Source:

- Frame camera → U-Net → lane mask (frame masuk ke u-net)
- Mask → boundary extraction (mengunah area lane menjadi garis tepi)
- Boundary → curve fitting (menghaluskan boundery)
- Curve → tangent angle (menentukan arah lajur relatif terhadap kendaraan)

Final Output:

- Steering Angle (degree)
- Steering Voltage (V)

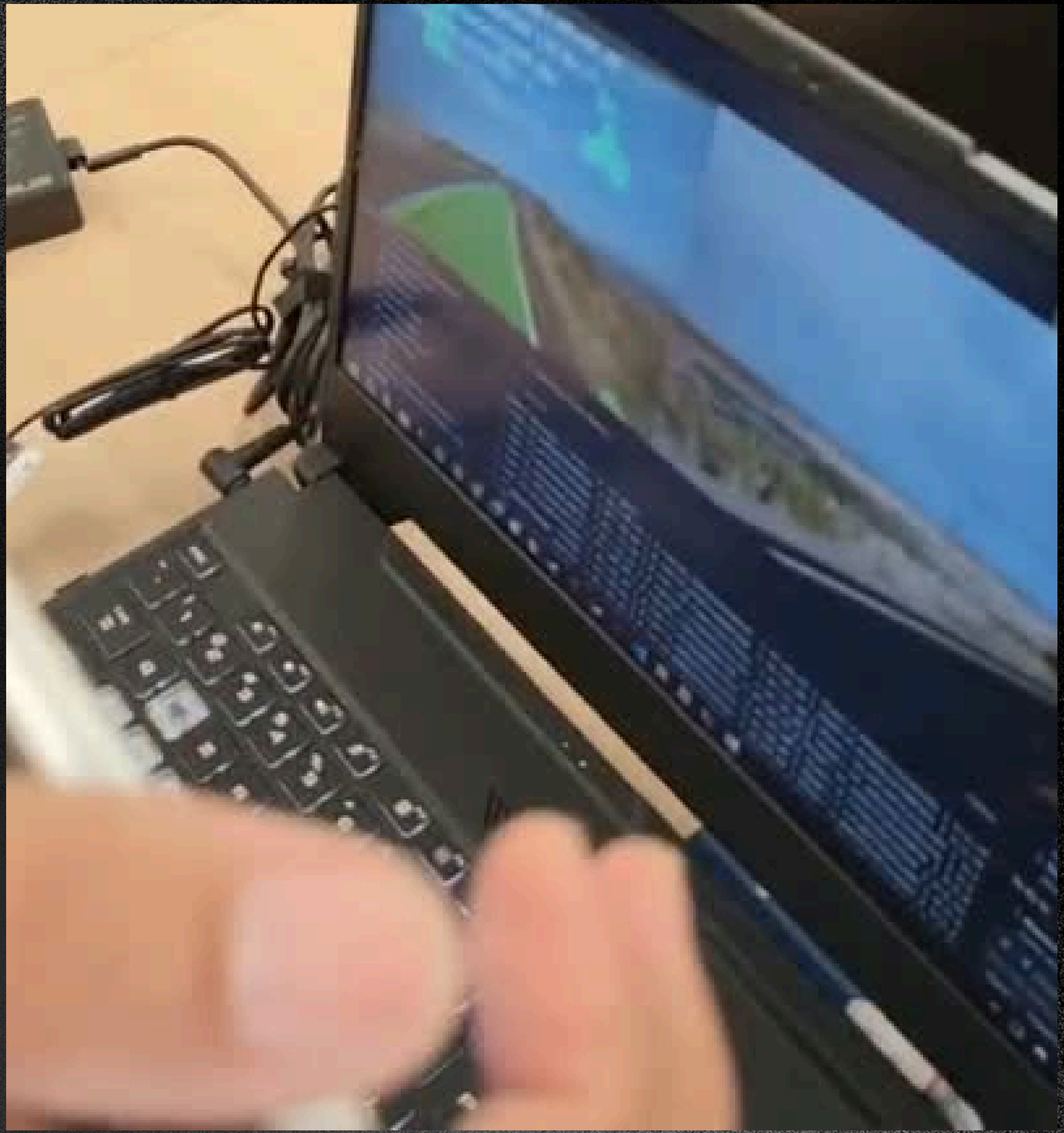
Validation & Results

- Masking visualizes drivable lane area
- Curved lane boundaries extracted
- Kalman Filter smooths angle fluctuation
- Steering output stable even on curved roads
- Observed Benefit:
- Reduced noise
- More realistic steering respons

Conclusion

- Vision-based lane detection combined with Kalman Filter
- Demonstrates practical sensor fusion for vehicle control

Results



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Autonomous Vehicle

System Overview

Latar Belakang:

- Steering merupakan komponen utama lateral control pada autonomous vehicle
- Estimasi sudut kemudi

Tujuan

- Menghasilkan Estimated Steering Angle
- Berbasis stereo vision secara independen

Overview Sistem

Stereo Camera → Perception → Estimation → Control → Actuation (eps)

Project Component

Stereo Camera

- Dua kamera (Left & Right)
- Digunakan untuk: Lane detection , Heading and curvature estimation

Microcontroller : esp32

Sensing

- Stereo Camera (Left–Right)
- Input visual lingkungan jalan

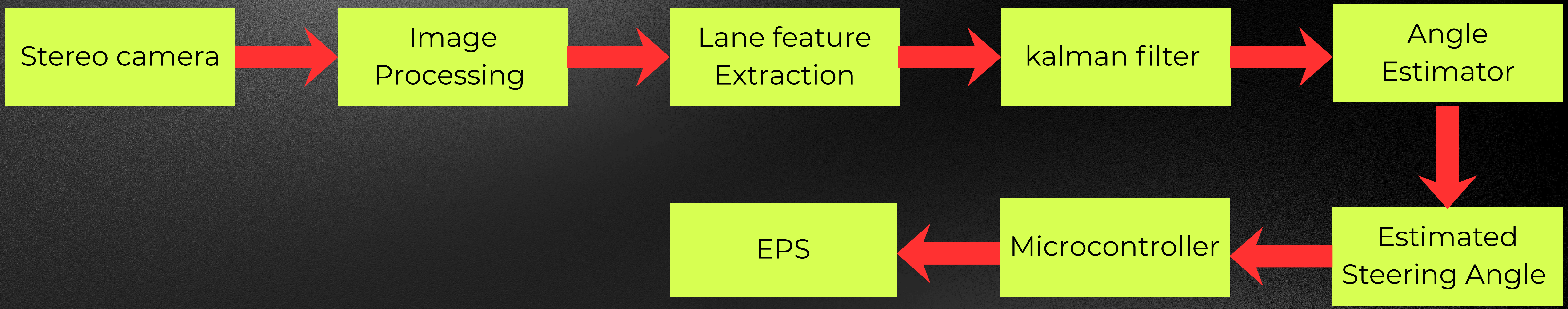
Perception

- Image preprocessing
- ROI (Region of Interest) pada area jalan
- Road & lane masking

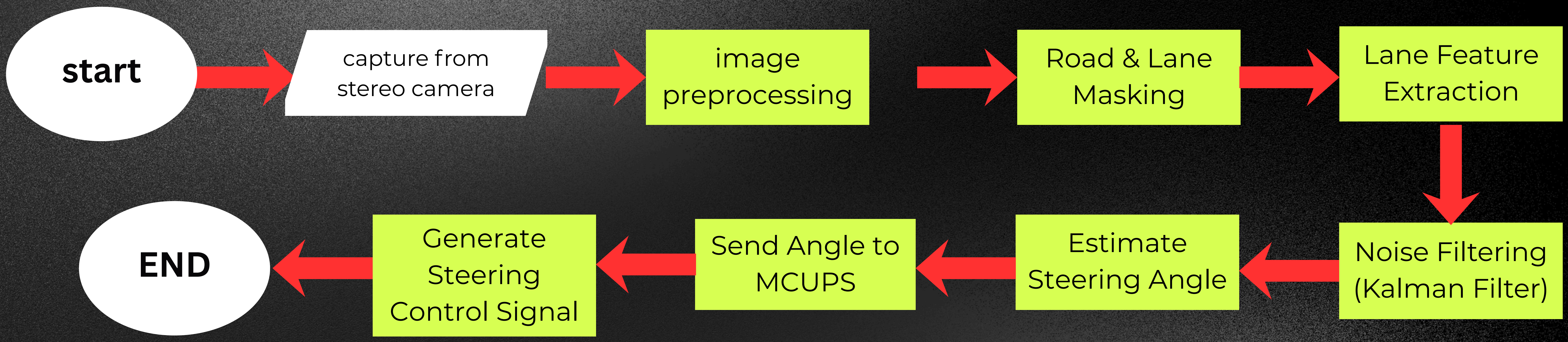
Control & Output

- Estimated Steering Angle :
  - MCU (Microcontroller Unit)
  - contoh: ESP32
- MCU menghasilkan:
  - PWM (Pulse Width Modulation)
- Digunakan untuk aktuator steering (nema23)

Block Diagram



Flowchart


start
capture from stereo camera
image preprocessing
Road & Lane Masking
Lane Feature Extraction
Noise Filtering (Kalman Filter)
Estimate Steering Angle
Send Angle to MCUPS
Generate Steering Control Signal
END

Journey

- Unable to give input signals to eps and eps controller
- using esp as microcontroller and to give input for the stepper
- tb660 as the stepper motor driver
- next improvement make the computer vision , sensor fusion and autonomous steering to be synchronize

Model Evaluation

- Good accuracy and masking for lane segmentation and angle curvature
- Adaptor material for stepper should be improve
- Evaluation confirms the model is reliable for lane detection, but **in wet road model is unreliable due to reflection.**

Validation & Results

- Masking visualizes drivable lane area
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Validation & Results

Thank YOU